



Phylogenomic analysis of disease-resistance proteins in plants

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Challenges in protein classification

1. Remote homolog detection.
How much information does knowing a remote homolog provide?
2. Phylogenetic context is critical.
Paralogs can have divergent function (so can orthologs...)
3. Domain structure issues.
4. Some fraction of the annotations in the sequence databases are not exactly accurate.

Function and Structure Prediction by Homology

If you have a sequence you know nothing about,
find a relative.

Given one member, find the
relatives...



Would we recognize this member?



Homolog identification and profile construction
helps differentiate critical features from variable

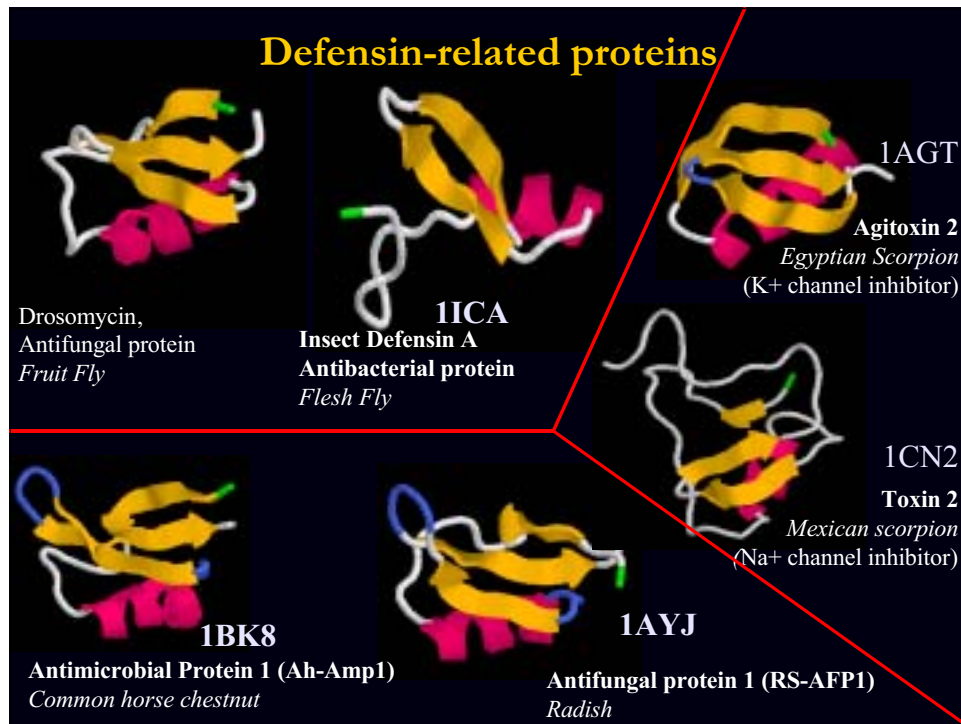




Profile
generalization
allows us to
identify some
truly remote
relatives

**“Evolution conserves structure
and function”**

But not completely.

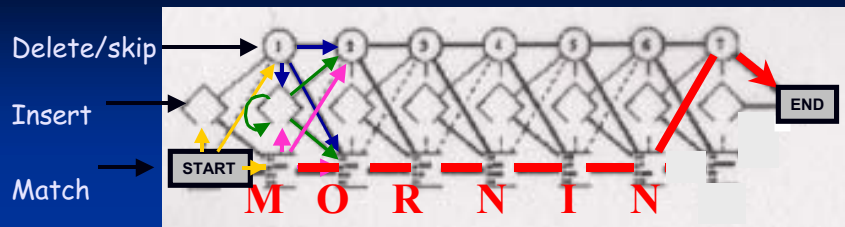


Why not just use BLAST?

Poor performance in remote
homolog detection compared to
HMM methods.

Park, J., Karplus, K., Barrett, C., Hughey, R., Haussler, D., Hubbard, T. & Chothia, C. Sequence comparisons using multiple sequences detect three times as many remote homologues as pairwise methods. J. Mol. Biol. 284, 1201-1210 (1998).

Hidden Markov Model (HMM)



Originally used in speech recognition (Rabiner, 1986)

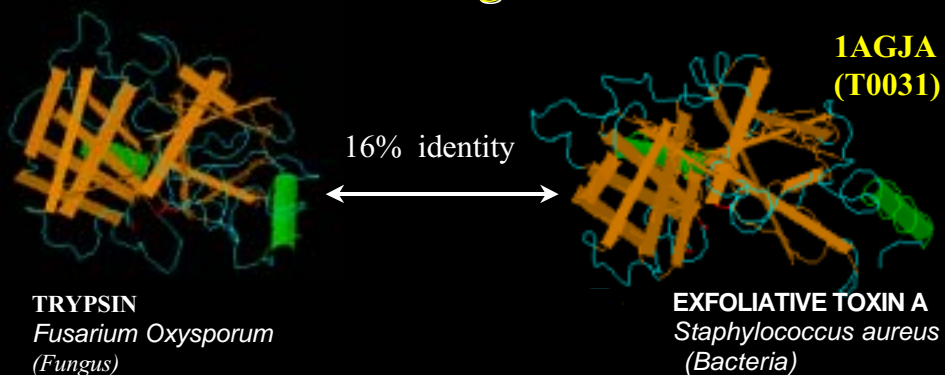
Proposed for DNA modeling (Churchill, 1989)

Applied to modeling proteins (Haussler et al, 1992)

- Multiple sequence alignment
- Identification of related family members ("homologs")

Hidden Markov Models in Computational Biology: Applications to Protein Modeling. Krogh, Brown, Mian, Sjolander and Haussler, *J.Mol. Biol.* (1994)

Homolog recognition in the Twilight Zone CASP2 Target T0031



For homolog recognition in the Twilight Zone, we need to know:

Which positions are critical?

Where can we allow deletions or mutations?

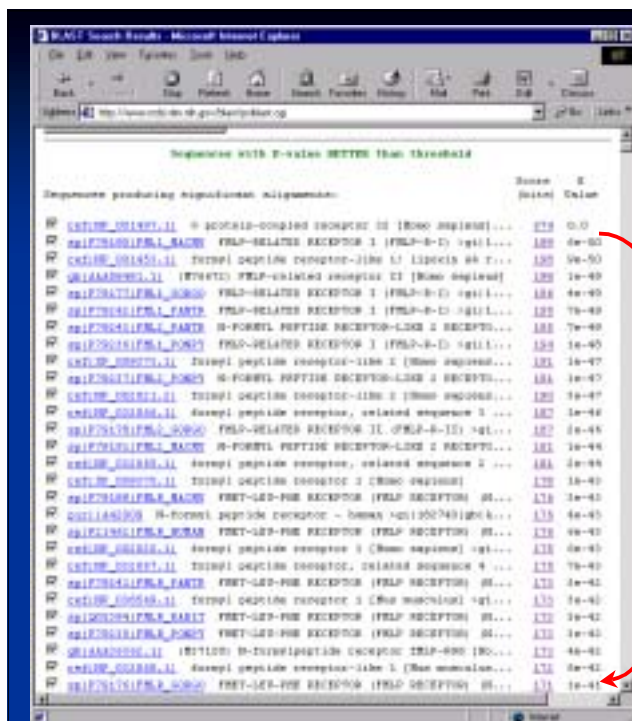
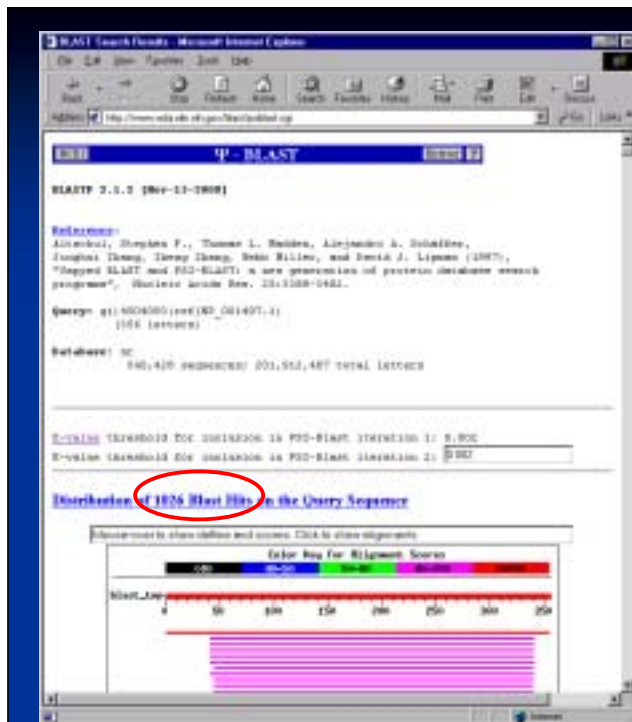
Homolog detection is just the first step...

Correct functional classification requires attention to evolutionary relationships

Example 1: Orphan GPCR classification

The screenshot shows the NCBI Sequence Viewer interface in Microsoft Internet Explorer. The address bar displays the URL: http://www.ncbi.nlm.nih.gov/entrez/query.fcgi?cmd=Retrieve&db=Protein&list_uids=4504093&opt=GenPept. The NCBI logo is visible at the top left. The search results show a single entry: **NP_001497 G protein-coupled receptor 32 [Homo sapiens]**, which is circled in red. Below the entry, the following details are listed:

Field	Value
LOCUS	NP_001497 356 aa PRI 31-OCT-2000
DEFINITION	G protein-coupled receptor 32 [Homo sapiens].
ACCESSION	NP_001497
PID	g1504093
VERSION	NP_001497.1 GI:4504093
DBSOURCE	REFSEQ: accession MN_001506.1



Or a chemokine receptor?

Or a C5A Anaphylatoxin chemotactic receptor?

Or...?

Or a novel type of receptor?

Another reason to not rely
on pairwise sequence similarity

What if the top-scoring match is
incorrectly annotated?

Example 2: Errors in database annotations

NCBI Sequence Viewer - Microsoft Internet Explorer

Address: http://www.ncbi.nlm.nih.gov/entrez/query.fcgi?cmd=Retrieve&db=Protein&list_uids=3541547&dopt=GenPept

NCBI Protein

Search: Protein for [] Go Clear

Display: Defline HTML Raw Add to Clipboard

AACC82381 putative odorant receptor LOR3 [Lampetra fluviatilis]

LOCUS AACC82381 352 aa VRT 02-DEC-1998

DEFINITION putative odorant receptor LOR3 [Lampetra fluviatilis].

ACCESSION AACC82381

PID g3941547

VERSION AACC82381.1 GI:3941547

DBSOURCE locus AF069346 accession [AF069346.1](#)

KEYWORDS

SOURCE European river lamprey.

COMMENTARY [Lampetra fluviatilis](#)

The top matching BLAST hits are also putative odorant receptors

Results for RID 904260375-29090-30487 - Microsoft Internet Explorer

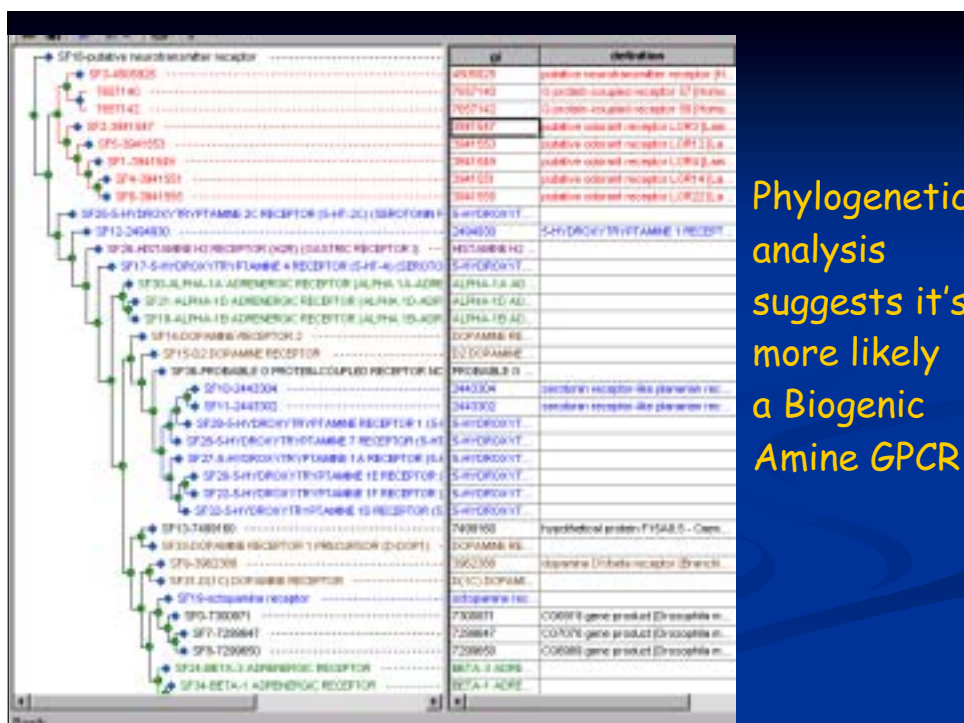
File Edit View Favorites Tools Help

Back Forward Stop Refresh Home Search Favorites History Mail Print Edit Di

Address http://www.ncbi.nlm.nih.gov/blast/blast.cgi

Sequences producing significant alignments:

		Score	(bits)	Val
gi 3941547 gb AACB2381.1	(AF069546) putative odorant recep...	633	0.0	
gi 3941549 gb AACB2382.1	(AF069547) putative odorant recep...	232	6e-60	
gi 3941553 gb AACB2384.1	(AF069549) putative odorant recep...	194	1e-48	
gi 3941551 gb AACB2383.1	(AF069548) putative odorant recep...	185	9e-46	
gi 4505925 ref NP_003958.1	putative neurotransmitter recep...	172	8e-42	
gi 7657142 ref NP_055441.1	G protein-coupled receptor 58 [...	167	2e-40	
gi 7657140 ref NP_055442.1	G protein-coupled receptor 57 [...	166	3e-40	
gi 3646424 emb CAA09599.1	(AJ011370) serotonin 4 receptor ...	160	2e-38	
gi 3326989 emb CAA73108.1	(Y12506) 5-HT4 receptor [Homo sa...	156	3e-37	
gi 12326004 emb LC423363.1	(AF028883) 5-hydroxytryptamine...	156	3e-37	



Lessons from CASP2



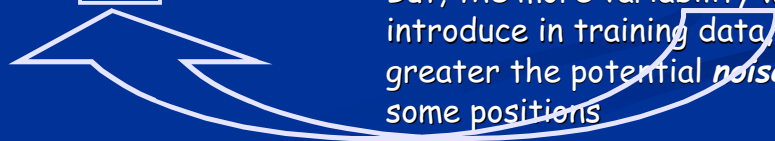
1. HMMs optimized for remote homolog detection generally require clustering and alignment of many divergent sequences.

2. Alignments of new sequences to these HMMs can be pretty awful.

Given a protein sequence ("target"), predict its most likely fold, and produce an alignment of the target and the solved structure. Predictions judged using structure-structure alignment (SCOP, VAST, DALI).

Conflict

D	S	L	E	M	K	I
D	S	I	E	M	K	V
D	T	I	W	M	K	M
D	T	I	W	M	K	L
D	T	V	W	M	K	F
D	T	F	R	K	K	I
D	T	F	R	K	K	V



- For effective *remote homolog* detection, a profile or HMM needs information from divergent family members
- Without this context, we cannot differentiate critical from variable positions
- HMMs constructed with such data provide a coarse classification
- But, the more variability we introduce in training data, the greater the potential *noise* at some positions

Subfamily HMM construction

How to build Subfamily HMMs (SHMMs)

1	D	S	L	F	M	K	I
2	D	S	I	F	M	K	V
3	D	T	I	W	M	K	M
4	D	T	I	W	M	K	L
5	D	T	V	W	M	K	F
6	D	T	F	R	K	K	I
7	D	T	F	R	K	K	V



Share statistics between subfamilies where there is evidence of a common distribution.

Keep statistics separate at positions where there is evidence of **divergent** structure.

Improved specificity, sensitivity, alignment accuracy

Step 1: Form Dirichlet Mixture Posterior

At each position, for each subfamily, construct a Dirichlet mixture *posterior*, by combining the Dirichlet mixture *prior* with the amino acids aligned at that position by that subfamily.

(Weighted) subfamily counts

Mixture coefficient

Component Parameters

$$q_j := P(\vec{\alpha}_j \mid \vec{n}, \Theta^{\text{Prior}})$$

$$\alpha_{ji} := \alpha_{ji} + n_i$$

(Weighted) subfamily counts of amino acid i

Step 2: Calculate family contribution

Other subfamilies contribute, proportional to the probability of the amino acids they aligned at that position, given the revised Dirichlet mixture density.

D	S	L	F	M	K	I
D	S	I	F	M	K	V
D	T	I	W	M	K	M
D	T	I	W	M	K	L
D	T	V	W	M	K	F
D	T	F	R	K	K	I
D	T	F	R	K	K	V

$$f_i = \sum_{s' \neq s} P(\vec{n}_{s'} \mid \Theta^{\text{Post}}) n_{s'i}$$

(Weighted) counts from subfamily s_{-}

(Formula for computing Prob ($n \mid _$) are in Sjolander et al, 1996)

Step 3: Compute pseudocounts

Add the family contribution to the observed (weighted) counts, to obtain the pseudocounts t_i of amino acid i :

$$t_i = n_{si} + f_i$$

(Weighted) subfamily counts
for subfamily s

family
contribution

Step 4: Compute amino acid probabilities

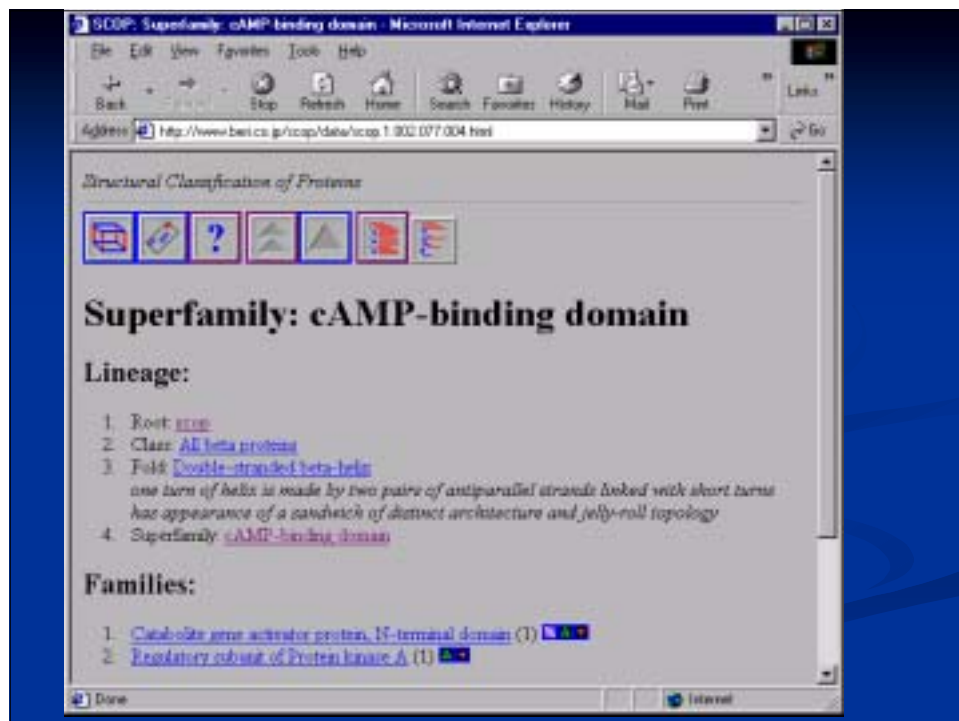
Normally, we compute amino acid probabilities by combining a Dirichlet mixture prior with observed counts as follows:

$$\hat{p}_i = \sum_j P(\bar{\alpha}_j | \bar{n}) \frac{n_i + \alpha_{ji}}{|\bar{n}| + |\bar{\alpha}_j|}$$

Instead, we will estimate the probability of amino acid i as follows:

$$\hat{p}_i = \sum_j P(\bar{\alpha}_j | \bar{n}) \frac{t_i + \alpha_{ji}}{|\bar{t}| + |\bar{\alpha}_j|}$$



Subfamily HMM Performance



The screenshot shows a Microsoft Internet Explorer window with the title "SCOP: Superfamily: cAMP-binding domain - Microsoft Internet Explorer". The address bar displays the URL "http://www.birc.co.jp/scop/data/scop.1.902.007.004.html". The page content is titled "Structural Classification of Proteins" and features a navigation bar with icons for Home, Search, Favorites, History, Mail, Print, and Links. The main heading is "Superfamily: cAMP-binding domain". Below this, the "Lineage:" section lists the following hierarchy:

1. Root: [scop](#)
2. Class: [All beta proteins](#)
3. Fold: [Double-stranded beta-helix](#)
one turn of helix is made by two pairs of antiparallel strands linked with short turns has appearance of a sandwich of distinct architecture and jelly-roll topology
4. Superfamily: [cAMP-binding domain](#)

The "Families:" section lists the following entries:

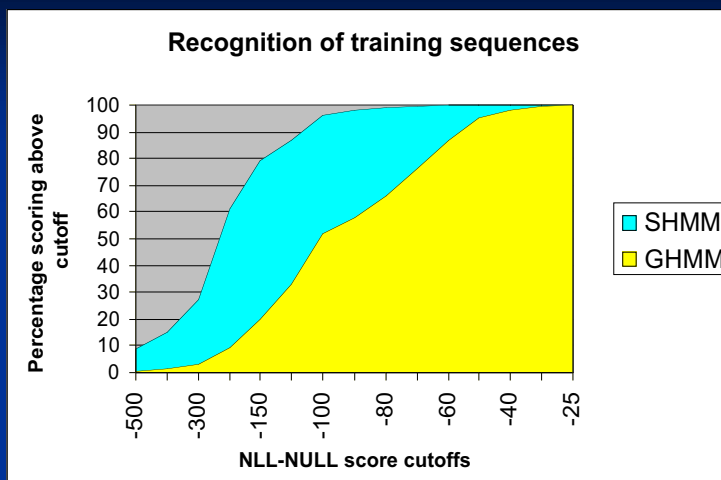
1. [Catabolic gene activator protein, N-terminal domain](#) (1) 
2. [Proximate subunit of Protein kinase A](#) (1) 

The browser window shows standard navigation buttons (Back, Forward, Stop, Refresh, Home, Search, Favorites, History, Mail, Print, Links) and a status bar at the bottom indicating "Done" and "Internet".

Socrates' First Command: Know Thyself

Test 1. How accurate are subfamily HMMs at recognizing their own training sequences?

Test 1: Training Sequence Recognition



% sequences found above cutoffs: SHMM method 100%
GHMM method 99.89%

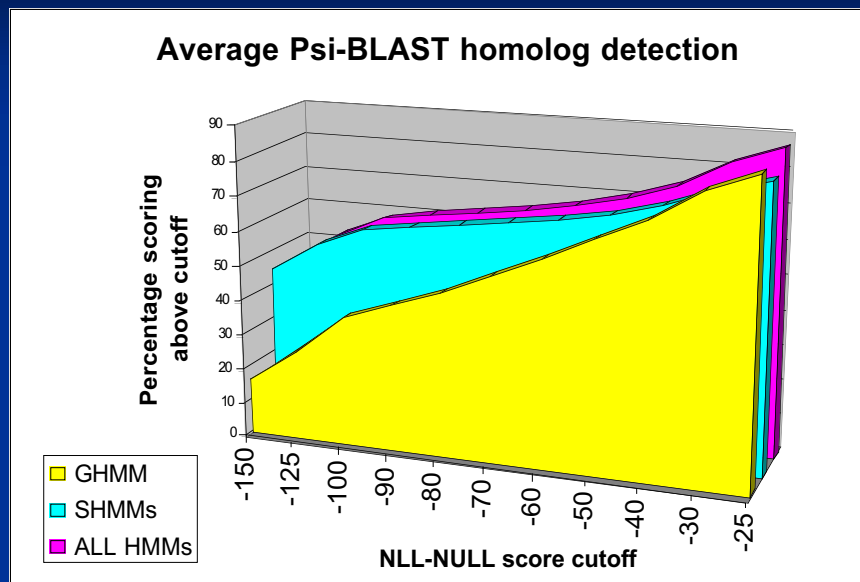
Error (first family assignment): 25/0.4/5 (-2.6/1.000)

Honor thy father and thy mother

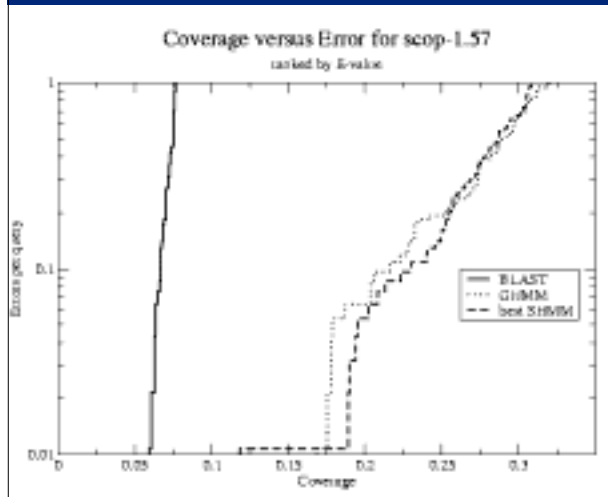
*and thy brothers and sisters
and aunts and uncles
and cousins
and second cousins
and third cousins twice removed...*

Recognition and classification of
family members

Test 2: PSI-BLAST homolog detection Average Per Family



Subfamily HMMs improve homolog detection (relative to BLAST or a single HMM for the family)

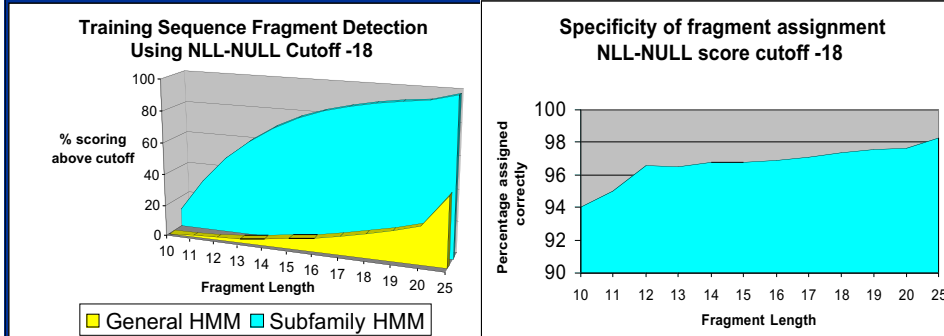


PDB40 dataset 4,013 seqs
For each structure, homologs were gathered and aligned using SAM-T99 (from UCSC). A general HMM for each family was constructed from each alignment using Karplus sequence weighting and Dirichlet mixture densities. Subfamily HMMs were created from the same alignment. All PDB40 sequences were scored against each cluster, and assigned a general HMM score and the best Subfamily HMM (SHMM) score. Scores were sorted by significance. Homologs are determined by the SCOP database.

Fragments and ESTs can be especially challenging



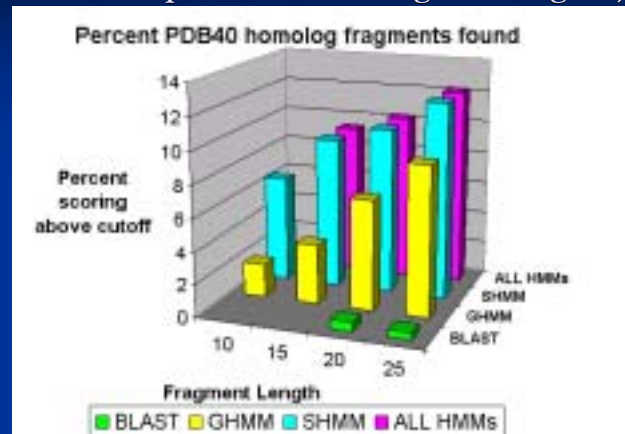
Training sequence fragment detection



PDB40 experiments.

Fixed cutoff chosen to provide zero FP for sequence lengths ≤ 25

PDB40 homolog fragment detection (HMM score and BLAST cutoffs chosen to give zero false positives for all fragment lengths)

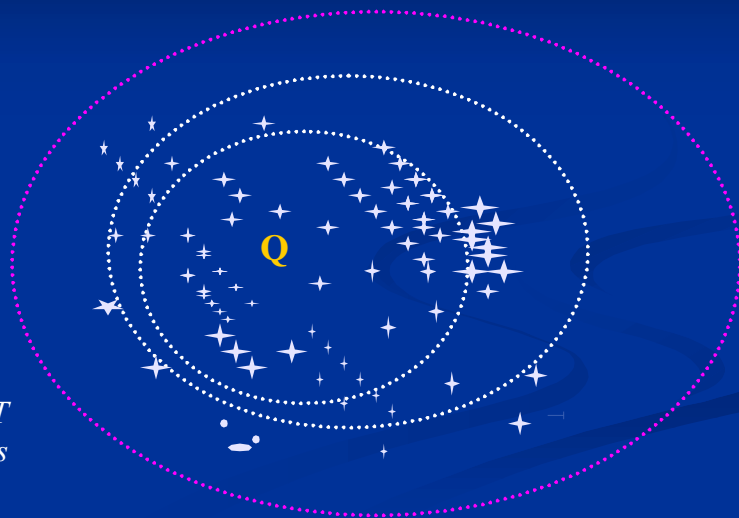


	10	15	20	25
Subfamily HMM / ALL:	6.59%	9.36%	10.28%	12.16%
General HMM:	2.06	3.69	6.81	9.25
BLAST:			0.57	0.43

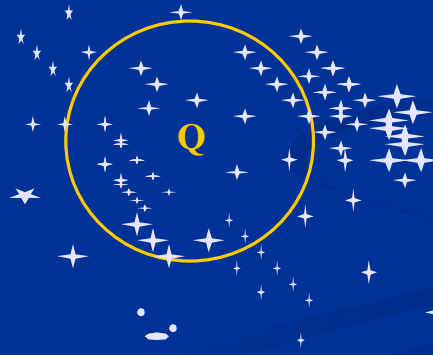
FlowerPower

Iterative clustering and alignment tool

Step 1: Identify putative homologs to
query sequence (Q)



Step 2: Select initial training set

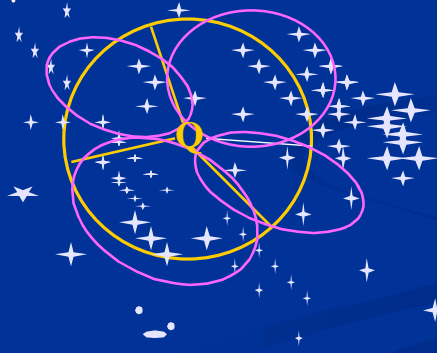


Step 3: Align initial set, identify subfamilies, and build subfamily HMMs.

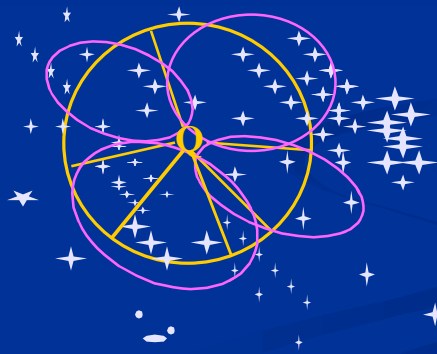


Step 4: Identify and align new homologs.

1. Search with subfamily and general HMMs.
2. Accept hits above threshold.
3. Align accepted hits to closest HMM.



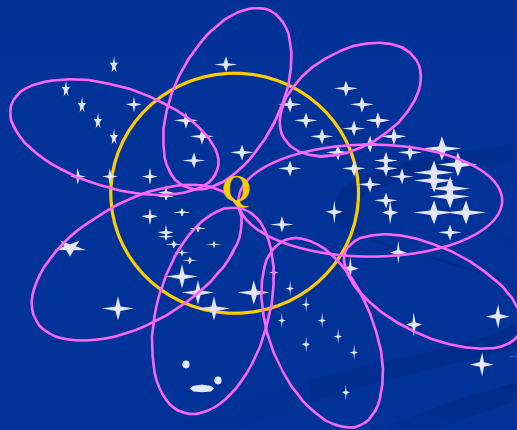
Step 5: Run BETE to identify subfamilies, and build new subfamily HMMs.



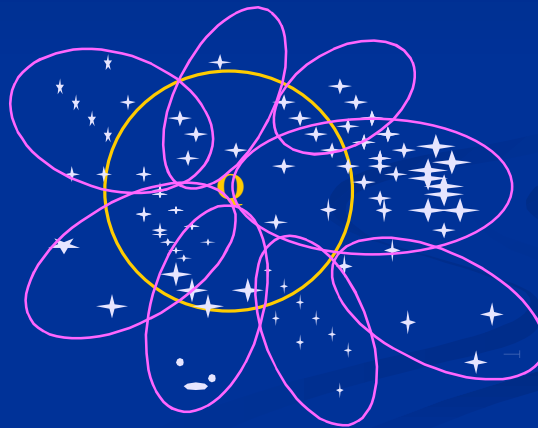
Step 6: Iterate



until ...

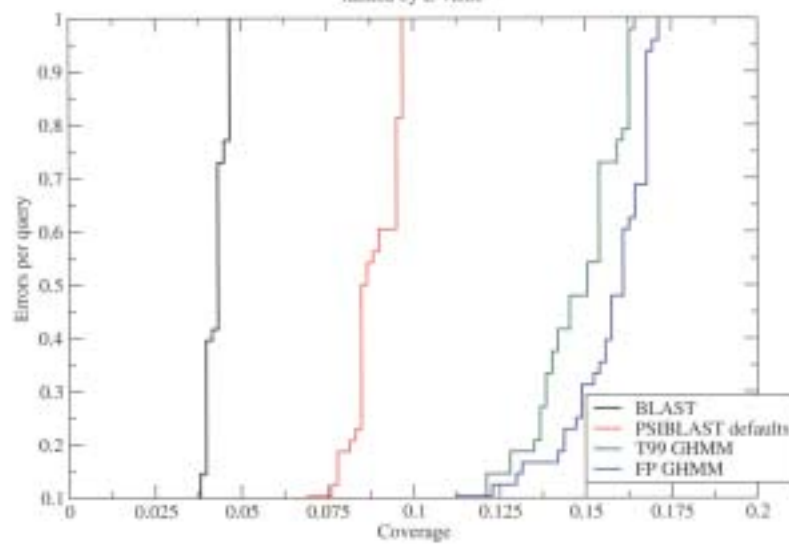


convergence.



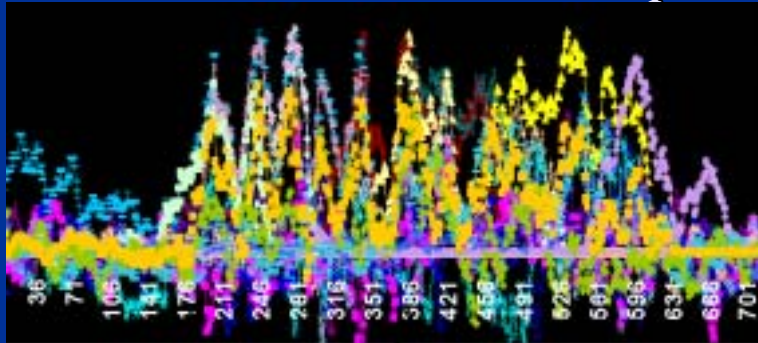
HMM performance improves with improved alignments (Preliminary results)

Coverage versus Error for scop-1.57
ranked by E-value

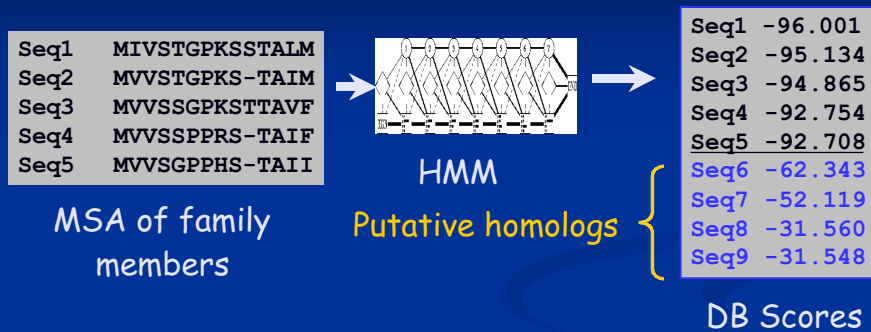


A Tale of Two Domains

Hidden Markov models,
Potassium channels,
Excursions in the Twilight Zone
and some stories about startups...



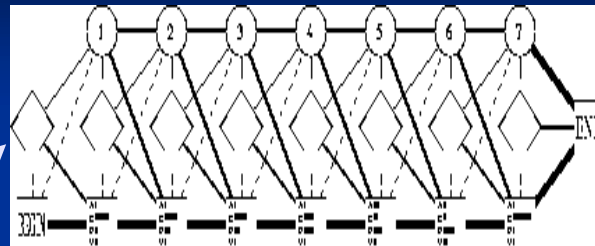
Step 1: Build an HMM, and identify putative homologs



Underlying assumption: Domain-level matches to the HMM will cluster in specific regions, while sequence fragments will align over HMM uniformly.

Step 2: Align database hits to HMM

```
>Seq6
MIVSTSG
>Seq7
MVVTTG
>Seq8
SP
>Seq9
PP
```



Seq6	M	I	V	S	T	S	G
Seq7	M	V	V	-	T	T	G
Seq8	-	-	-	-	-	S	P
Seq9	-	-	-	-	-	P	P

(Alignment to subfamily HMMs can improve results)

Step 3: Create Affinity (log odds) vectors

Seq6	M	I	V	S	T	S	G
Seq7	M	V	V	-	T	T	G
Seq8	-	-	-	-	-	S	P
Seq9	-	-	-	-	-	P	P

Alignment of
database hits

Seq6	3.3	3.2	3.3	3.4	3.5	1.5	2.8
Seq7	3.3	3.1	3.3	0.0	3.5	1.6	2.8
Seq8	0.0	0.0	0.0	0.0	0.0	1.5	5.0
Seq9	0.0	0.0	0.0	0.0	0.0	3.4	5.0

Log likelihood
(Affinity)
vectors

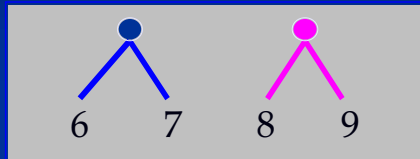
$$L[s,p] = \log \frac{\text{Prob}(s_p | \text{HMM})}{\text{Prob}(s_p)}$$

s_p = amino acid aligned by
sequence s at position p .
Define $L[s,p] = 0$ when s_p is a gap

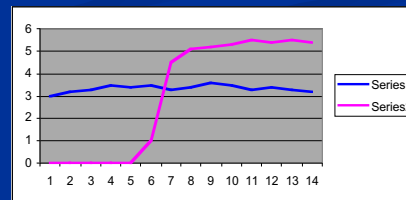
Seq1	M	I	V	S	T	G	P
Seq2	M	V	V	S	T	G	P
Seq3	M	V	V	S	S	G	P
Seq4	M	V	V	S	S	P	P
Seq5	M	V	V	S	G	P	P

Alignment used as basis for HMM

Step 4: Cluster affinity vectors



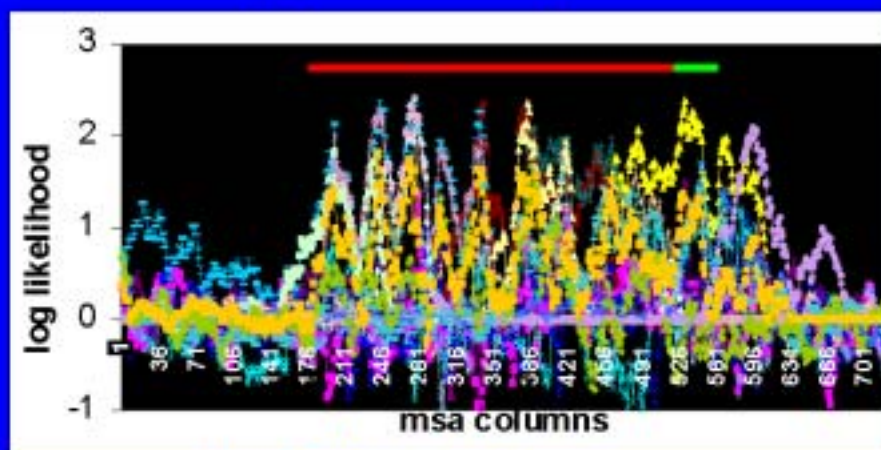
Clustering of vectors
Agglomerative clustering
Euclidean distance
Cluster termination cutoff



Plot LL clusters
(simple average)



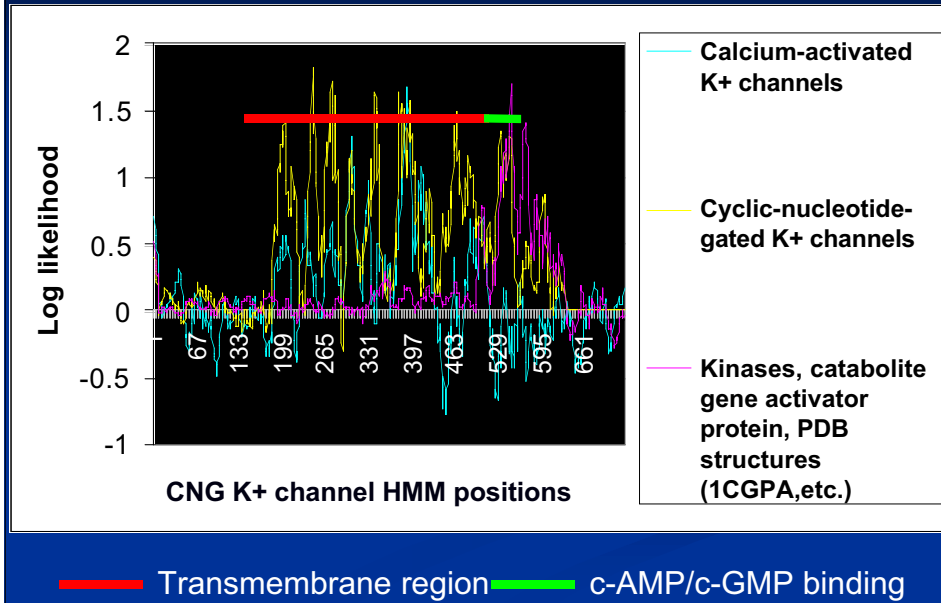
Cyclic-Nucleotide-Gated K⁺ Channel HMM Alignment Analysis



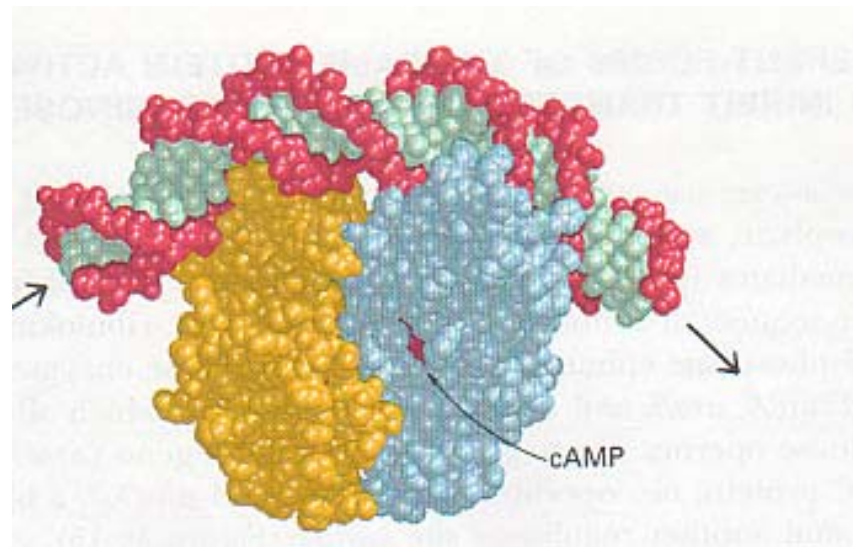
Transmembrane region
c-AMP/c-GMP binding

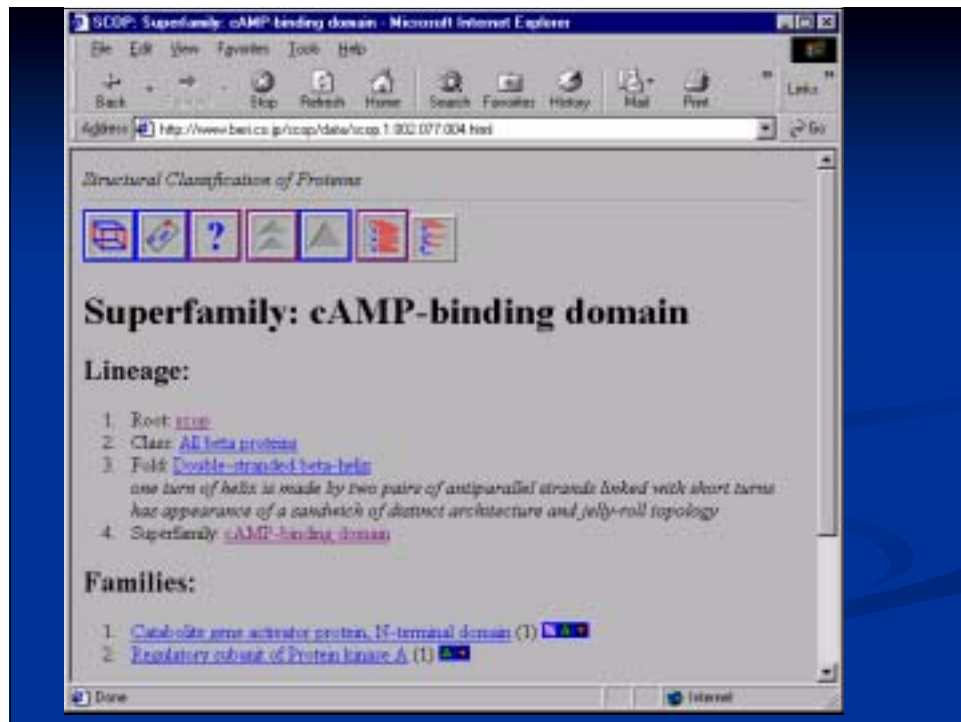
MAS p23

Analysis of CNG K⁺ domain structure



Catabolite Gene Activator Protein (CAP) bound to DNA





Database hits to Voltage-gated K⁺ channel

	gi 3023481 sp CIKB_RAT	-427.39
	gi 3913257 sp CIKB_HUMAN	-426.47
	gi 348462 pir A44838	-425.46
	gi 345875 pir S31761	-423.14
	gi 3023495 sp CIKA_HUMAN	-422.38
	...	
	gi 1147595 emb CAA64176.1	-32.56
	gi 3874832 emb CAA94204.1	-32.50
	gi 487428 gb AAA50173.1	-32.49
	gi 3452399 gb AAC32857.1	-32.41
	gi 2648884 gb AAB89577.1	-32.39
	gi 2832781 emb CAA12645.1	-32.34
	gi 1255396 gb AAA96127.1	-32.13
	gi 116452 sp P15389 CIN5_RAT	-32.09
	gi 3924830 emb CAA98957.1	-31.74
	gi 465874 sp P34410 TWK8_CAEL	-31.55
	gi 2315751 gb AAB66175.1	-31.48
	gi 2665784 gb AAC29515.1	-31.48
	gi 2315752 gb AAB66176.1	-31.45
	gi 2315635 gb AAB66084.1	-31.28
	gi 1707203 gb AAB37942.1	-31.23
	gi 1181413 gb AAC96618.1	-31.21
	gi 3881291 emb CAA21749.1	-31.14

Ion channels

Similar to TNF-alpha-induced protein B12

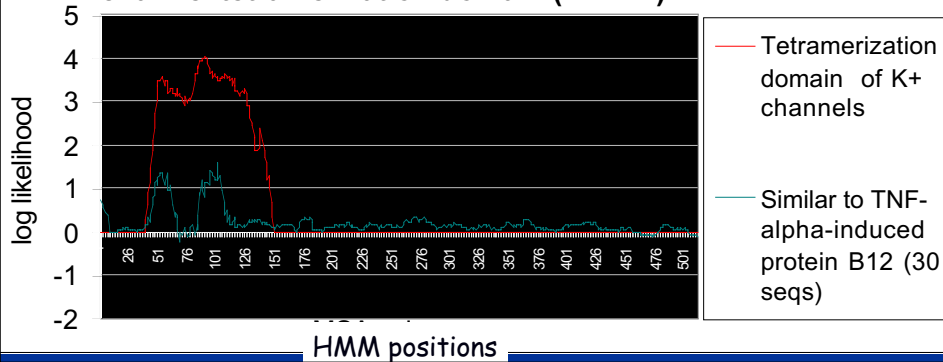
Unknown

?

Analysis of Voltage-gated K⁺ channels domain structure



TNF-alpha-induced protein B12 and K⁺ channel tetramerization domain (1T1DA)



TNF-alpha acts on K⁺ current...but how?

PubMed search results for 'Effects of tumor necrosis factor on inward potassium current and cell morphology in cultured human oligodendrocytes'.

Effects of tumor necrosis factor on inward potassium current and cell morphology in cultured human oligodendrocytes

McLennan JG, Mishkova M, Kuo SY

Department of Pharmacology and Therapeutics, Faculty of Medicine, University of Toronto, Canada

The effects of recombinant human tumor necrosis factor- α (rhTNF- α) on inward potassium current and cell morphology have been studied in cultured human oligodendrocytes. The effects of rhTNF- α on inward potassium current were studied using a patch-clamp technique. Treatment of oligodendrocytes with rhTNF- α (10 ng/ml) resulted in a significant decrease in the amplitude of the inward potassium current. This effect was blocked by the TNF- α receptor antagonist, soluble TNF- α receptor (sTNF-R1). The effect of rhTNF- α on cell morphology was also studied. Treatment of oligodendrocytes with rhTNF- α resulted in a significant decrease in cell area. This effect was also blocked by sTNF-R1.

PubMed search results for 'Tumor necrosis factor enhancement of transient outward potassium currents in cultured rat cortical neurons'.

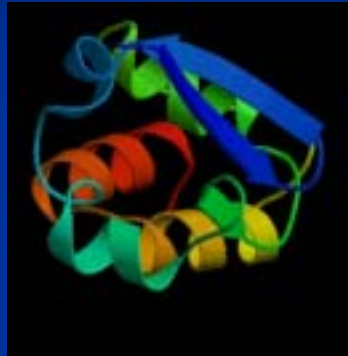
Tumor necrosis factor enhancement of transient outward potassium currents in cultured rat cortical neurons

Kimura H, Kikuchi A, Kamei M, Shiga K, Tachibana E

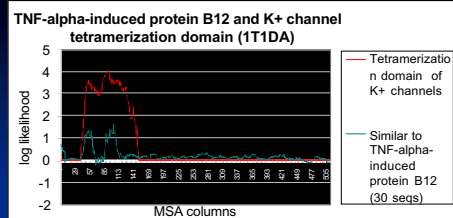
Department of Pharmacology, Hokkaido University School of Medicine, Sapporo, Japan

The effect of recombinant human tumor necrosis factor- α (rhTNF- α) on voltage-gated potassium currents of cultured neurons derived from embryonic rat cerebral cortex was studied using the whole-cell patch-clamp technique. Treatment of neurons with rhTNF- α resulted in an increase in transient outward potassium current density, dependent upon the concentration of rhTNF- α and the incubation time, without affecting other membrane currents such as barium and 4-aminopyridine-sensitive currents. Long exposure (12–48 h) to rhTNF- α (10 ng/ml) increased transient outward potassium current (A current) density without affecting the parameters of persistent and slow-deactivation currents. Binding of rhTNF- α to its receptor was demonstrated by increasing effect on the A current. Since the increase of A current density induced by rhTNF- α is abolished by both the anti-TNF- α receptor antibody and cycloheximide treatment, the effect of rhTNF- α might be mediated through receptors and by de novo synthesis of the channel proteins and/or modulating proteins associated with the channel proteins. It is concluded that rhTNF- α enhances transient outward potassium current (A current) density in cultured rat cortical neurons. It is likely that rhTNF- α acts on the channel proteins and/or modulating proteins associated with the channel proteins.

Predictions:



1T1DA
Tetramerization Domain
of K⁺ channels

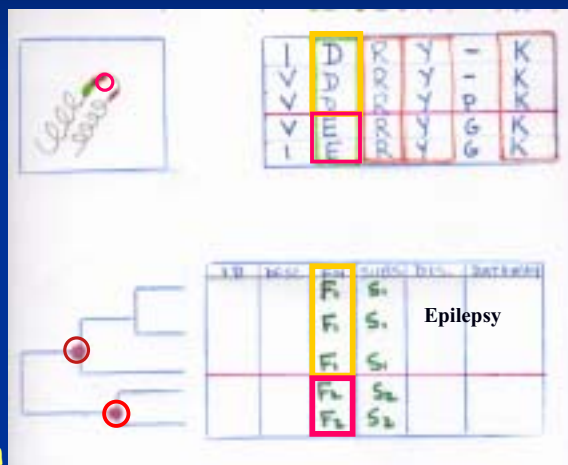


- Structure of TNF-alpha induced protein B12 is homologous to K⁺ channel tetramerization domain
- Does TNF-alpha induced protein B12 affect K⁺ channel function by interacting with the K⁺ channel T1 domain?

Web server for high-throughput functional classification of proteins

3D
structure
viewer

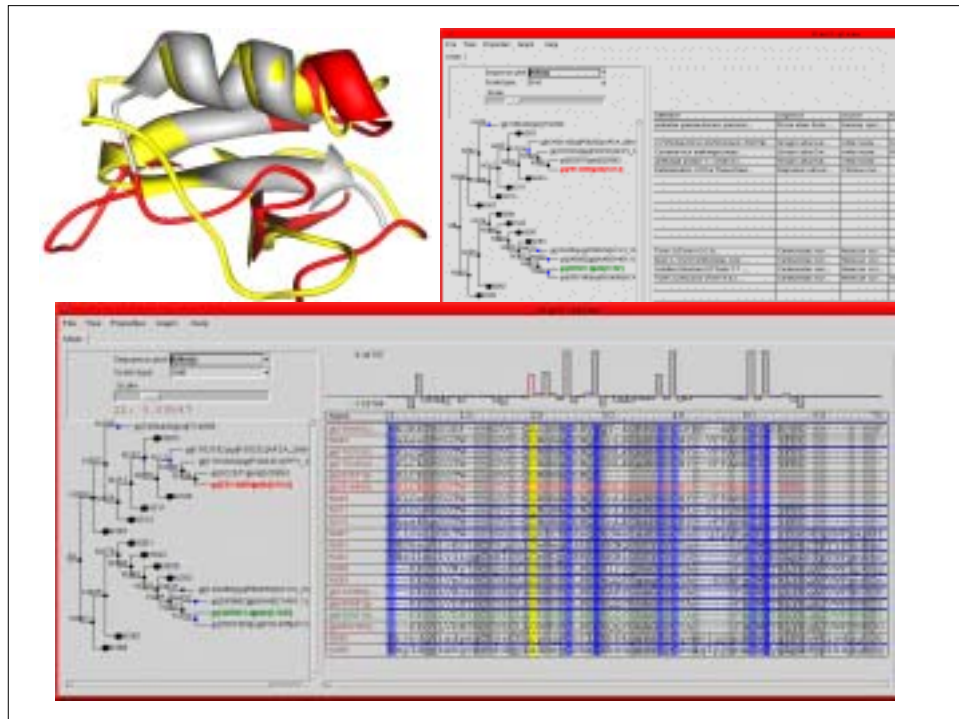
Phylogenetic
tree, with
subfamily
decomposition



Multiple
sequence
alignment

Attribute
data table

Enable and foster virtual collaborations, scientific discovery,
correction of errors in database annotations.



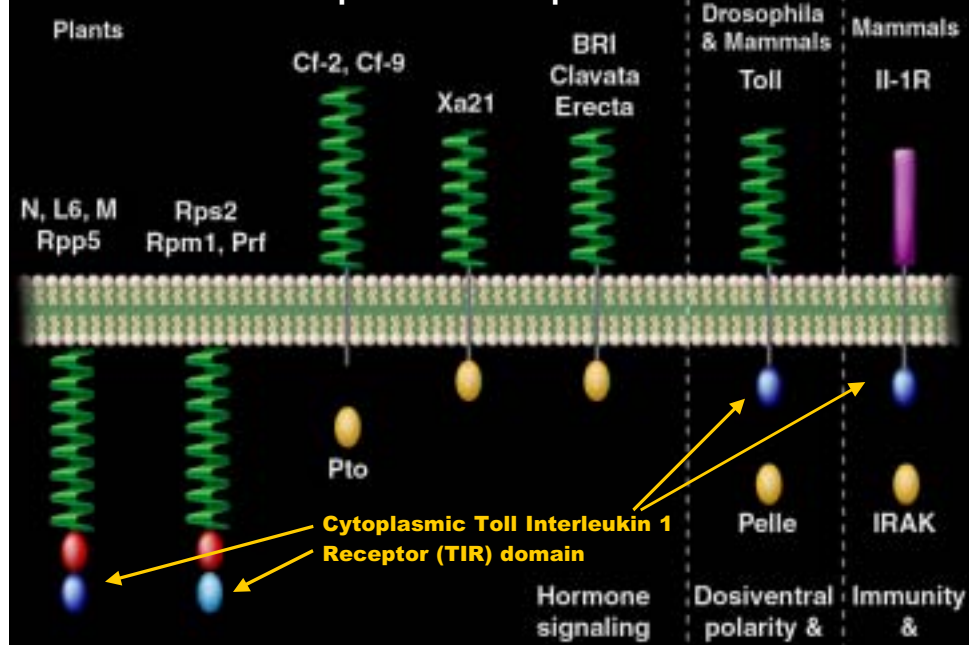
Stalking disease-resistance proteins in rice



Toll Interleukin 1 domain
PDB structure 1FYX

Joint work with Barbara Baker and Brian Staskawicz

Plant and Animal Innate Immunity Mediated by Structurally Similar Receptor and Receptor-like molecules



Conserved “scaffolding” proteins in cell death



CARD: CAspase Recruitment Domain

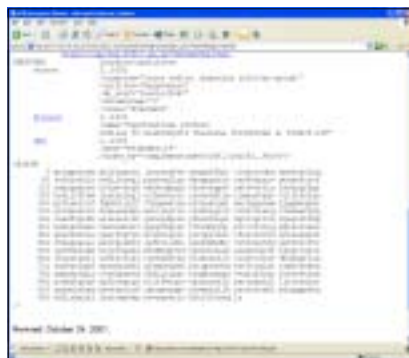
Nod is implicated in Crohn's disease

N is involved in plant Hypersensitive Response (HR)

TIR domains missing from monocot species...



Monocot sequences are absent from the TIR subfamily
 TIR domain is a novel protein domain found in the TIR subfamily of the TIR domain superfamily
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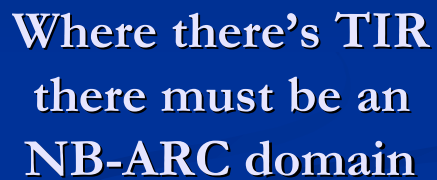


Searching the rice
 genome with general
 and subfamily HMMs
 for the TIR domain...

gi|14587298 gets top score (e-12 to TIR structure)

Query	Hit	Score	Length	Score	Score	Score	Score	E-value
gi 14587298 cd 14587298.1	cd 14587298.1	11.540	150	-30.000	-30.000	-30.000	-30.000	1.140e-12
gi 14587298 cd 14587298.1	cd 14587298.1	11.540	150	-30.000	-30.000	-30.000	-30.000	1.140e-12
gi 14587298 cd 14587298.1	cd 14587298.1	11.540	150	-30.000	-30.000	-30.000	-30.000	1.140e-12
gi 14587298 cd 14587298.1	cd 14587298.1	11.540	150	-30.000	-30.000	-30.000	-30.000	1.140e-12
gi 14587298 cd 14587298.1	cd 14587298.1	11.540	150	-30.000	-30.000	-30.000	-30.000	1.140e-12

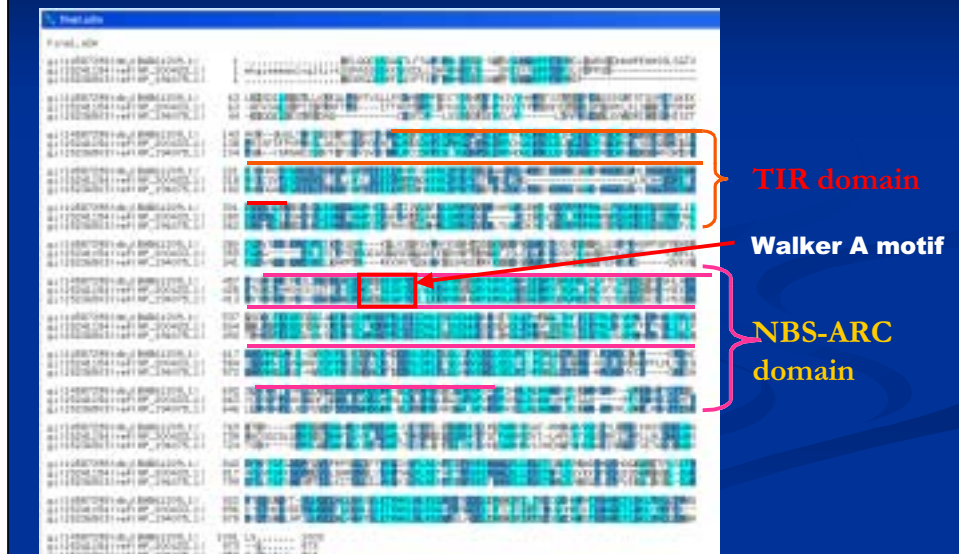
Alignment of rice sequence to Toll-like receptor 2 (TLR2) subfamily



BLAST fails to detect TIR domain homologs for this sequence



Clustering and aligning homologs with FlowerPower



UC Berkeley Phylogenomics

Group Members:

David Kondering, Ph.D.

Wayne Christopher, Ph.D.

Bob Edgar, Ph.D.

Austin Huang

Joseph Dale



Investigation of plant disease-resistance proteins

Brian Staskawicz

Barbara Baker

Richard Michelmore

Thanks to the National Science Foundation

<http://phylogenomics.berkeley.edu>

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